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Measuring Cross-Channel Ad Synergy with Machine Learning: TV, Social, and Search Integration

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Abstract

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This article examines how cross-channel ad synergy is currently measured when TV, social, and search are integrated in a single campaign, and what role machine learning plays in that measurement. In increasingly fragmented media environments, advertisers suspect that exposures across channels interact rather than simply add up, but existing evidence and tools are scattered and often channel centric. The study conducts a systematic literature review of peer-reviewed articles published between 2019 and 2023, focusing on research that applies machine learning or advanced data-driven methods to multi-channel advertising settings. The reviewed studies are coded by channel configuration, data sources, modelling approach, treatment of synergy or interaction effects, and outcome metrics. The findings show that machine learning is widely used for targeting, prediction, and multi-touch attribution, but that explicit modelling of synergy among TV, social, and search is rare, often methodologically fragile, and highly context dependent. The article concludes by outlining a research agenda for causal, interaction-aware machine learning frameworks for cross-channel ad synergy.

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1. Introduction

Cross-channel advertising has become central to contemporary media strategy as consumers move fluidly between television, social platforms, and search engines within the same decision journey. Rather than evaluating each touchpoint in isolation, advertisers increasingly seek to understand whether and how impressions on one channel amplify the impact of others, creating synergistic effects on outcomes such as brand awareness, engagement, and conversion. Emerging evidence suggests that integrated campaigns can generate meaningful cross-effects, for example when offline and online formats jointly shape customer response trajectories (Lesscher et al., 2021; Unnava & Aravindakshan, 2021). Yet, despite growing investments in integrated media plans, robust metrics for "ad synergy" across TV, social, and search remain underdeveloped and unevenly applied in practice.

Traditional measurement approaches, such as single-channel attribution rules or aggregate marketing-mix models, struggle to capture the high-dimensional, dynamic interactions that characterize modern multi-channel campaigns. Recent work demonstrates that cross-channel effects can unfold at fine temporal resolutions, for instance when TV exposures immediately change the responsiveness of sponsored search advertising (Liu & Hill, 2021). At the same time, the proliferation of user-level impression logs, second-by-second TV data, and rich social media engagement traces calls for analytical tools that can learn complex patterns and interaction effects from large-scale paths to conversion rather than pre-specifying simple functional forms (Romero Leguina et al., 2020).

Machine learning and artificial intelligence are increasingly positioned as key enablers of such granular measurement. Studies show that supervised learning models can extract actionable customer insights from social media data and improve targeting performance, highlighting their capacity to model non-linear relationships and high-dimensional features (Arasu et al., 2020). Broader reviews of AI in advertising emphasize the role of advanced algorithms in optimizing targeting, personalization, and ad delivery across digital environments (Gao et al., 2023), while digital and social media marketing scholarship stresses the need to align these technologies with evolving customer journeys and platform ecosystems (Dwivedi et al., 2021). In parallel, multi-touch attribution research proposes increasingly sophisticated, data-driven frameworks, including path-based attribution models, to assign credit across multiple impressions and channels (Gaur & Bharti, 2020; Romero Leguina et al., 2020).

However, this literature remains fragmented. Many studies focus on a single dominant environment (such as social platforms) or treat channels generically, without explicitly isolating the joint contribution of TV, social, and search within integrated campaigns. Evidence on cross-channel dynamics is often context-specific, relying on bespoke quasi-experiments or platform datasets that are difficult to generalize beyond the original setting (Liu & Hill, 2021; Lesscher et al., 2021; Unnava & Aravindakshan, 2021). There is limited synthesis regarding how "synergy" is operationalized, which machine learning architectures are used to model it, what metrics are employed to evaluate incremental gains, and under what data conditions each approach is viable.

Against this backdrop, the present study conducts a systematic literature review of peer-reviewed research published between 2019 and 2023 that applies machine learning to measure or infer cross-channel advertising effects, with a particular focus on the integration of TV, social, and search. The review aims to map how cross-channel ad synergy is conceptualized, identify dominant data sources and modelling strategies, and assess the strength and consistency of empirical evidence for synergistic effects in multi-channel campaigns. By consolidating dispersed findings and highlighting methodological and substantive gaps, the study seeks to provide an integrative foundation for future work on machine learning-based measurement of cross-channel ad synergy and to inform practitioners seeking more reliable guidance on allocating budgets across TV, social, and search.

2. Literature Review

Research on cross-channel advertising increasingly emphasizes that media effects are interdependent rather than additive, with exposure in one channel shaping how audiences respond in others. Empirical work shows that offline and online tools such as direct mail and display advertising can reinforce each other across the funnel, generating positive synergy effects rather than simple duplication (Lesscher et al., 2021). Similarly, studies comparing online display and paid search to offline advertising find that digital channels do not merely substitute for traditional media but can amplify their impact on firm performance when coordinated within an integrated campaign architecture (Bayer et al., 2020). These findings suggest that evaluating TV, social, and search in isolation risks underestimating their joint contribution to brand and sales outcomes.

In parallel, the literature on digital customer journeys has documented how consumers move fluidly between devices and platforms, leaving dense trails of digital signals that reflect awareness, consideration, and purchase intentions across multiple channels. Schweidel et al. (2022) show that such signals span paid, owned, and earned touchpoints, and that their combined configuration often explains outcomes better than any single channel metric. This reinforces calls to move beyond siloed media metrics toward path-based and system-level perspectives on communication effectiveness (Romero Leguina et al., 2020). However, much of this work remains descriptive or relies on aggregated data, which limits the ability to isolate incremental and interaction effects for specific channel combinations such as TV plus search or TV plus social.

Machine learning and AI-driven analytics provide tools to address these complexity and interaction challenges. In social and digital environments, machine learning models have been used to optimize targeting, creative, and budget allocation by learning non-linear patterns from high-dimensional exposure data (Arasu et al., 2020; Dwivedi et al., 2021; Gao et al., 2023). Within attribution modelling, scholars describe a shift from heuristic rules toward data-driven and algorithmic approaches that explicitly account for multi-channel paths, carryover, and interaction effects (Gaur & Bharti, 2020; Denisenko & Grineva, 2021). These reviews and conceptual contributions highlight that multi-touch attribution and related modelling techniques are increasingly expected to integrate a wide range of signals across channels and devices rather than focusing on single-touch or single-channel effects.

Despite these developments, several gaps remain at the intersection of cross-channel synergy and machine learning. First, most empirical work on synergy examines offline-online pairs such as direct mail and display or focuses on general digital portfolios, rather than full-funnel combinations involving TV, social, and search that dominate contemporary media planning (Lesscher et al., 2021; Unnava & Aravindakshan, 2021). Second, attribution and journey-modelling studies often concentrate on purely digital paths and do not systematically incorporate TV impressions or GRPs into modelling pipelines, which constrains their ability to capture how broadcast exposure primes responses to search queries and social interactions (Liu & Hill, 2021; Schweidel et al., 2022). Third, while AI and machine learning are widely discussed as enablers of granular and adaptive measurement, there is limited conceptual integration between these methods and cross-channel strategy questions such as optimal sequencing, frequency allocation, and budget synergies across TV, social, and search (Bayer et al., 2020; Gao et al., 2023).

Building on these streams, this study systematically reviews how prior research has measured cross-channel advertising effects, how multi-touch attribution and related machine learning approaches have been applied, and to what extent existing models explicitly quantify synergy among TV, social, and search. In doing so, it aims to bridge the gap between channel-level measurement and integrated planning and to outline a research agenda for machine learning-based approaches that can better capture, explain, and exploit cross-channel ad synergy. To summarize the most relevant prior work underpinning this review, particularly studies on cross-channel synergy, customer-journey measurement, and algorithmic attribution, Table 2.1 synthesizes key references and their main findings.

Table 2.1 Prior Research

No	Author(s) & Year	Article Title	Research Findings
1	Bayer et al. (2020)	The Impact of Online Display Advertising and Paid Search Advertising Relative to Offline Advertising on Firm Performance and Firm Value	The study finds that both online display advertising and paid search advertising have positive effects on firm performance, measured by sales, and on firm value, measured by Tobin's q, based on proprietary annual advertising expenditure data from 1,651 firms over seven years. Relative to offline advertising, paid search shows a stronger positive effect on sales, consistent with its proximity to purchase decisions and its enhanced targeting capabilities, whereas display advertising shows a

			stronger positive effect on Tobin's q, consistent with more long-term value effects. Overall, the results indicate that the economic benefits of advertising are heterogeneous across channel types, with direct implications for how managers assess advertising effectiveness and how external stakeholders evaluate firm performance.
2	Gaur & Bharti (2020)	Attribution Modelling in Marketing: Literature Review and Research Agenda	The paper reviews attribution modelling studies from 1990-2019 using a PRISMA-based approach and classifies the literature by constructs, channel use, and modelling techniques. It finds that most work appears in high-quality journals (71% in ABDC A*/A) and that publications surged in 2014-2019 (67% of articles). The most common methods include

			Markov chain, probit, and linear models, and the authors propose an ensemble framework combining Markov chain properties with Shapley value to improve robustness.
3	Liu & Hill (2021)	Frontiers: Moment Marketing: Measuring Dynamics in Cross-Channel Ad Effectiveness	The study provides causal empirical evidence that "moment marketing," which synchronizes sponsored search advertising in real time with offline events such as TV ads, can improve the effectiveness of search advertising. Leveraging large exogenous variation in TV advertising spending over a long period and granular consumer search data under relatively stable search advertising strategies, the authors show that TV-moment-based search advertising can be effective not only for TV-advertised brands but also for

			their competitors. They further document the underlying mechanism: TV ads change the quality of subsequent search traffic, including who searches, where they search, and how they search, which alters how the average searcher responds to later search results and ads.
4	Denisenko & Grineva (2021)	Analysis of Attributional Modeling Methods in Marketing	The article defines the concept of attribution modeling in digital marketing and explains its role in estimating how each touchpoint in a customer's digital path contributes to conversion. It then reviews and describes a range of modern attribution modeling methods that have emerged alongside improvements in collecting and aggregating user-level web data. Finally, it compares these approaches by outlining the main advantages and

			disadvantages of each, showing that different models involve trade-offs and that the question of which attribution method is best remains unsettled.
5	Lesscher et al. (2021)	Do Offline and Online Go Hand in Hand? Cross-Channel and Synergy Effects of Direct Mailing and Display Advertising	The article finds that direct mailing produces significant cross-channel effects by increasing online consumer activity, including online search and clicking behavior, based on quasi-experimental evidence from a large European insurance firm. It also shows that direct mailing is effective across the entire purchase funnel, generating both direct and indirect effects and leading to a positive net sales impact. In a second study using field experiment data, the authors demonstrate positive synergy between direct mailing and display advertising, indicating that

			direct mail remains effective not only on its own but also when combined with digital marketing tools.
6	Schweidel et al. (2022)	How Consumer Digital Signals are Reshaping the Customer Journey	The article argues that consumer digital signals are reshaping the customer journey and that firms can gain competitive advantage by detecting and acting on these signals to improve journey management and personalization. It also highlights a tension between privacy concerns and personalization benefits, suggesting that willingness to emit observable signals may depend on the strength of the consumer–firm relationship, and it closes with a research agenda for consumers, firms, and regulators.
7	Gao et al. (2023)	Artificial Intelligence in Advertising: Advancements,	The study reviews how AI is applied in advertising across four core areas, targeting,

		Challenges, and Ethical Considerations in Targeting, Personalization, Content Creation, and Ad Optimization	personalization, content creation, and ad optimization, and uses VOSviewer to map how these themes are connected in the computational advertising literature. It finds that targeting and personalization are tightly linked in determining which ads are shown to which audiences, content creation supports personalization by generating appealing ad materials, and ad optimization builds on the first three elements to adjust delivery in pursuit of higher ROI. The review also highlights major challenges and pressing ethical concerns associated with current AI-driven advertising practices and calls for more responsible and effective use of these technologies.

3. Methods

This study employs a systematic literature review to synthesize current knowledge on measuring cross-channel advertising synergy with machine learning, focusing on the integration of TV, social, and search. The review targets peer-reviewed journal articles published between 2019 and 2023 to capture recent developments in both media measurement and machine learning techniques. Searches were conducted in major academic databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, and relevant marketing and information systems journals. Combinations of keywords were used around four main concept clusters: cross-channel or multichannel advertising, TV or television, social media and search advertising, and machine learning, artificial intelligence, or advanced analytics. To be included, articles had to be written in English, published in peer-reviewed journals, and contain an empirical or conceptual focus on measuring or modelling advertising effects across more than one channel, with at least one digital channel and a clear methodological component involving machine learning or related data-driven techniques. Conference papers, non-peer-reviewed reports, purely conceptual essays with no methodological detail, and studies that examined only single-channel performance without any cross-channel dimension were excluded.

The screening process followed a structured sequence. First, titles and abstracts were reviewed to remove clearly irrelevant records and ensure that studies addressed advertising or communication effects rather than unrelated forms of analytics. Second, the remaining articles underwent full-text assessment to confirm that they addressed cross-channel or multichannel settings and provided sufficient methodological information on machine learning, attribution, or path-based modelling. The final corpus was coded using a standardized template that captured study context (industry, geography, data sources), channel configuration (including whether TV, social, and search were explicitly modelled), machine learning or modelling approach, operationalization of synergy or interaction effects, and key outcome measures such as brand metrics, engagement, or conversions. Coding was iteratively refined to ensure consistency and to enable comparison across studies, forming the basis for the thematic synthesis reported in the results and discussion sections.

4. Results and Discussion

The reviewed studies indicate that measurement of cross-channel advertising effects is progressing, but work that explicitly targets synergy among TV, social, and search is still limited. Most empirical research models interactions either between offline and online channels or among different digital platforms, with relatively few studies incorporating all three focal channels in a unified framework. Evidence from campaigns that combine offline and online media shows that exposures in one channel frequently change responsiveness in another, supporting the idea of genuinely multiplicative rather than purely additive effects (Bayer et al., 2020; Lesscher et al., 2021; Liu & Hill, 2021). Research on digital customer journeys also demonstrates that patterns of cross-channel information search and purchase vary substantially by category and consumer segment, implying that the potential for synergy depends on how consumers naturally combine channels such as search, social, and other online or offline sources (Szopiński et al., 2020; Schweidel et al., 2022).

Across the corpus, three main ways of conceptualizing synergy can be distinguished. Some studies define synergy behaviorally, as changes in downstream responses such as clicks, searches, conversions, or purchase intention when channels are combined compared with when they are used alone. Experiments and quasi-experiments show that coordinated use of media types can significantly increase engagement and purchase intention, for example when online broadcast media are paired with interactive formats (Gao & Zhao, 2021) or when direct mail is combined with display advertising (Lesscher et al., 2021). Other work operationalizes synergy statistically, using interaction terms in regression or panel models to test whether the marginal effect of one channel depends on exposure in another (Bayer et al., 2020; Liu & Hill, 2021). A third group of studies embeds synergy within broader omnichannel or journey constructs, examining how sets of paid, owned, and earned digital signals jointly shape progression through the funnel rather than isolating individual channels (Unnava & Aravindakshan, 2021; Schweidel et al., 2022). Only a small subset focuses specifically on the triad of TV, social, and search, and even fewer quantify their joint incremental impact using machine learning.

In terms of methods, the review reveals a gradual shift from aggregate, equation-driven approaches toward more data-driven and machine learning based techniques. Attribution and budget allocation studies increasingly adopt multi-touch frameworks that use historical path data to learn the contribution of different touchpoints rather than relying on heuristic rules (Gaur & Bharti, 2020; Romero Leguina et al., 2020; Denisenko & Grineva, 2021). In social and digital advertising contexts, supervised learning models, including tree-based ensembles and other non-linear methods, are used to predict response and optimize targeting based on high-dimensional exposure and behavioral features (Arasu et al., 2020; Gao et al., 2023). However, even where machine learning is applied, most implementations focus on predicting outcomes or improving campaign efficiency, while the measurement of cross-channel synergy is treated as a secondary diagnostic rather than a primary objective. Models rarely include explicit interaction structures or post-hoc decomposition that would quantify how TV exposures reshape the effectiveness of subsequent search and social impressions.

The review also highlights important issues around causality and identification. Studies that carefully account for selection, timing, and confounding show that cross-channel effects and synergies can be misestimated if underlying consumer heterogeneity and exposure patterns are not adequately modeled (Liu & Hill, 2021; Assael et al., 2021). For example, consumers who are already more engaged with a brand may both see more ads and search more frequently, which can lead naive models to overstate the incremental impact of particular channels. Similarly, cross-sectional or highly aggregated designs can obscure the sequence and timing of exposures, even though these dynamics are central to understanding synergy. These concerns are especially salient for machine learning approaches, which can produce accurate predictions without necessarily isolating causal effects. As a result, there is a growing call to integrate causal inference techniques, such as experiments, quasi-experiments, and uplift or treatment-effect modeling, into machine learning based measurement frameworks, particularly when assessing cross-channel synergies that inform budget shifts across TV, social, and search.

From a managerial and research perspective, these findings suggest both promise and gaps. Existing evidence supports the notion that coordinated use of multiple channels can generate synergies in attention, engagement, and conversion, and that machine learning methods are well suited to modeling high-dimensional exposure patterns across TV, social, and search. At the same time, the scarcity of studies that explicitly model all three channels together, the limited use of interaction-aware machine learning or causal ML, and the heterogeneity in how synergy is defined all restrict the generalizability of current insights. Future work would benefit from designing models that explicitly treat ad synergy as a focal construct, for example by estimating incremental lift surfaces across channel combinations and frequency levels, and from embedding experimental or quasi-experimental designs within machine learning pipelines. Such advances would provide more robust guidance on when and how integrated TV, social, and search campaigns generate synergy, and under what conditions that synergy is strong enough to justify strategic reallocation of media budgets.

5. Conclusion

This review concludes that machine learning has strong potential to improve how researchers and practitioners measure cross-channel ad synergy, but its application to integrated TV, social, and search campaigns is still limited and fragmented. Existing studies show that media channels often interact rather than simply add up, and that coordinated exposure can enhance awareness, engagement, and conversion more than isolated tactics. However, most models and frameworks studied were designed to predict outcomes or assign attribution at the level of individual channels, not to quantify synergy itself as a central construct.

At the same time, the underlying studies show important shortcomings that may reduce the validity and generalizability of current insights. Many rely on context-specific datasets, aggregated metrics, or observational designs that do not fully address selection effects, timing, or unobserved heterogeneity. As a result, it is reasonable for readers to question how far reported synergies reflect true incremental effects and how far they may be driven by pre-existing audience differences or unmeasured confounders. The focus on relatively narrow channel combinations and predominantly digital paths also limits our understanding of how TV, social, and search jointly shape consumer journeys in different industries and markets.

These limitations point to concrete directions for further research. Future studies should design models that place cross-channel synergy at the center of the analysis, with clear operational definitions and diagnostics for interaction effects across TV, social, and search. There is also a need for more longitudinal, experimental, or quasi-experimental designs that are combined with machine learning, so that flexible prediction is complemented by stronger causal identification. Finally, comparative work across categories, regions, and creative strategies would help clarify boundary conditions and show when integrated campaigns truly warrant reallocation of budgets. By explicitly acknowledging and addressing these gaps, subsequent research can provide more robust evidence and more reliable guidance for designing and optimizing cross-channel advertising strategies.

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